Self-Organised Transitions in Swarms with Turing Patterns

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1 Introduction

With swarm robotics relying heavily on local interaction it is important for the agents in the swarm to communicate suitable information. Individual agents are often inexpensive and may thus have limited individual capabilities, but, given a sufficient number of agents and efficient communication, the collective can perform complex actions at swarm level.

Many swarm approaches are based on self-organisation methods, which are usually inspired by nature (e.g. social insects [2]), for details see [5]. Our research is based on spatially self-organised natural phenomena, known from animal skin pattern formation [1]. These phenomena can be modelled by Reaction Diffusion systems that are known to produce the so-called Turing Patterns. We show here that these patterns are not restricted to physical and biological systems, but can also be used to shape the global structure of a robot swarm in a controllable manner.

2 Turing Patterns in Swarms

Swarm robotics relies upon local interaction for the swarm to interact within itself as well as with the environment. It has been recently reported that with the increase of the swarm size, error cascades can occur if information is communicated explicitly within the swarm [3]. A swarm may thus benefit from a communication scheme that is based on intrinsic information rather than on explicit information across the swarm. The distributed information is not available to each agent at any time, but will serve to guide the collective in a desired manner.

Reaction Diffusion (RD) systems describe the changes of measured concentrations of species in space over time, given how the components react with each other and that they will diffuse. Usually one species acts as an activator, u, and the other as an inhibitor, v. Our RD system is given by two coupled partial differential equations with the reaction terms being based on the Fitzhugh-Nagamo equations. The advantage of the RD system is that the diffusive aspect uses the second derivative meaning directionality is not required for the system.

If the system is setup so that the inhibitor is vanishing quicker than the activator, then patterns shall emerge, commonly known as Turing Patterns [8]. It has been shown that Turing Patterns can be created in physical agents [4], specifically in simulated Kilobots [7] (including initial random spatial distribution), and the next step is to attain a grounded understanding of the dynamics to allow for control by the swarm. We show some simple examples of parameter changes that allows for this.

3 Results

Stationary. The following results are for a stationary simulated Kilobot Swarm, see Fig. 1, using ARGoS [6], varying the diffusion constant of the activator and its self-interaction parameter slowly over time, see Fig. 2.

The swarm can attain different patterns, spots, stripes and inverted spots, given the parameters. We also show that the swarm, even with message loss, can change between patterns during the same simulation.

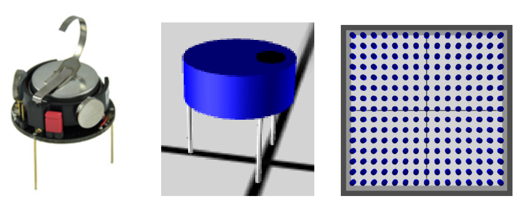

Figure 1: The Kilobot and it's simulated counterpart in ARGoS, and the grid setup used for the stationary initial results.

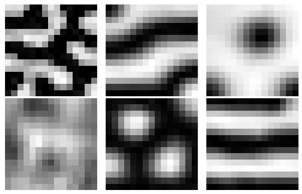

Figure 2: The top row shows the effects on the pattern as the activator's diffusion constant, D_u, increases over time. The bottom shows the pattern changes as λ, activator's self-interaction parameter, increases over time.

Non-Stationary. Unlike previous work mentioned so far, this set of results is if the RD system is continuing while the swarm is in motion. A simulator was created, using LiquidFun (`google.github.io/liquidfun/`) for the particle physics, to speed the experimental process at this stage. The motion is replicated to be similar to a Kilobot, forwards or semi-circle movements, and can sense in the same manner as the Kilobot. For this, however, there is nothing that the agents can sense, so their motions are entirely dependent on their activator's concentration values. This set of agents, unlike the Kilobots, have perfect communication.

Fig. 3 shows the preliminary result of setting two different values for diffusion constant of the activator.By setting only this parameter the swarm, while in motion, can form these patterns not only in their imagined space, but also in the physical space as well. The spots are easier to maintain, and even the agents change over time of who is the active parts of the pattern, the pattern itself deviates very little. The stripes on the other hand are less stable and requires, as seen in Fig. 3, the agents to be in closer proximity a lot longer. The stripes when formed are not stable for long, but this can be corrected, or at least maintain stability for longer, by changing the velocity rules of the agent.

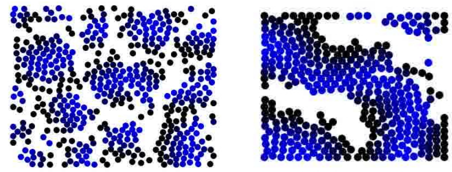

Figure 3: The left shows a swarm, of 500 agents with $D_u = 0.3$, forming spot patterns. The right is of a smaller swarm, 300 agents, with higher diffusivity, $D_u = 0.63$ forming stripes. The arena for the simulation on the right is smaller than that on the left.

4 Conclusion

Agents in a swarm receive a considerable amount of information regarding the collective and the environment through local interactions. Therefore, models that describe spatial self-organisation in nature are interesting in the context of robot swarm applications. Not only is it possible to have the swarm realise the desired pattern through parameter choice, but also to switch between these patterns as part of the problem solving capabilities of the swarm. It has also been demonstrated that these patterns can be achieved with the swarm moving with each agent deciding its motion only based on its concentration of the activator, though at the moment it is unstable for stripe-like patterns to be maintained for long. Future work will include further research into the relation between the underlying RD dynamics and the function of heterogeneous swarms.

References

[1] R. A. Barrio and C. Varea. Non-linear systems. *Physica A: Stat. Mech. & Appl.*, 372(2):210 – 223, 2006.

[2] E. Bonabeau, G. Theraulaz, J. Deneubourg, S. Aron, and S. Camazine. Self-organization in social insects. *Trends in Ecology & Evolution*, 12(5):188 – 193, 1997.

[3] M. Gauci, M. E. Ortiz, M. Rubenstein, and R. Nagpal. Error cascades in collective behavior: A case study of the gradient algorithm on 1000 physical agents. In *Proc.*, AAMAS '17, pages 1404–1412, 2017.

[4] C. Imrie and J. Herrmann. *Self-organisation of Spatial Behaviour in a Kilobot Swarm*, pages 551–561. 2017.

[5] H. Oh, A. R. Shirazi, C. Sun, and Y. Jin. Bio-inspired self-organising multi-robot pattern formation: A review. *Robotics and Autonomous Systems*, 2017.

[6] C. Pinciroli, V. Trianni, R. O'Grady, G. Pini, A. Brutschy, M. Brambilla, N. Mathews, E. Ferrante, G. Di Caro, F. Ducatelle, et al. Argos: A modular, multi-engine simulator for heterogeneous swarm robotics. In *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 5027–5034. IEEE, 2011.

[7] M. Rubenstein, C. Ahler, and R. Nagpal. Kilobot: A low cost scalable robot system for collective behaviors. In *Robotics and Automation (ICRA), 2012 IEEE International Conference on*, pages 3293–3298. IEEE, 2012.

[8] A. M. Turing. The chemical basis of morphogenesis. *Sciences-cecm. usp. br*, 237:37 – 72, 1952.